PREDICTING FAILURES OF THE BRAZILIAN AIR FORCE TUCANO FLEET USING SURVIVAL ANALYSIS

THESIS

Luciana Mesquita Monteiro, Captain, Brazilian Air Force

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DEPARTMENT OF THE AIR FORCE
AIR UNIVERSITY

AIR FORCE INSTITUTE OF TECHNOLOGY

Wright-Patterson Air Force Base, Ohio

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LUCIANA MESQUITA MONTEIRO, B.Eng.

Captain, Brazilian Air Force

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Luciana Mesquita Monteiro, B.Eng.

Captain, Brazilian Air Force

Committee Membership:

Daniel W. Steeneck, Ph.D.
Advisor

Seong-Jong Joo, Ph.D.
Co-Advisor

AFIT-ENS-MS-19-M-139

Abstract

During the life of an aircraft, several failures may occur causing unplanned maintenance and costs of parts, labor, transportation, lost opportunities, and operations, among others. The prediction of these events becomes especially difficult for new airframes, since they do not have many flight hours or enough data to observe failures. This study analyzes and model the time between failures (TBF) of the Brazilian Air Force T-27 Tucano fleet by applying various non-parametric, semi-parametric, and parametric statistical models, to the TBF, such as the descriptive statistics, Kaplan-Meier estimators, Cox proportional hazards models, with or without frailty, and survival regression models, with or without frailty. The study concludes by proposing a failure model that can be applied to the new similar airframes.

To my family and friends.

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PREDICTING FAILURES OF THE BRAZILIAN AIR FORCE TUCANO FLEET USING SURVIVAL ANALYSIS

I. Introduction

Background

The life-cycle cost (LCC) of a product, such as an aircraft, is not limited to its acquisition cost: the LCC include the research and development, production and construction, operations and maintenance (O&M), and retirement and disposal costs (Fabrycky & Blanchard, 1991).

While the budget allocations for many defense programs around the world shrink (Hess & Fila, 2001), the cost of operating and maintaining systems increased substantially (Fabrycky & Blanchard, 1991), so it is becoming very difficult to support the acquisition programs and even the O&M costs, completely (Messias, 1999). As a result of the poor LCC management and budget restrictions, the average age of an airframe in the BAF fleet has increased. Thus, the operation of the BAF fleet has been extended to beyond their designed service life.

Much of today's BAF fleet suffers from problems with the obsolescence of parts and adequate maintenance of the degraded remaining parts (Hess & Fila, 2001; Messias, 1999). Achieving the required operational availability while meeting the satisfactory safety levels has become very expensive to the aging fleet (Messias, 1999). As the O&M costs may reach 60 percent of the total ownership costs (Messias, 1999), any improvement maintenance activities will save money and enhance the operational availability of the fleet.

One way to improve operations is to better forecast aircraft failures. During the life of an aircraft, components and systems failures may occur, requiring expensive and disruptive maintenance activities. The costs of the unplanned maintenance include parts, labor, tools, manuals, hangar slots, transportation, time, and operations, among others (Fabrycky & Blanchard, 1991). Hence, a better forecast of the failures of aircraft and their sub-systems can lead to management improvements and cost savings.

The collection and analysis of failure and repair data is directly related to the selection and specification of the best model to explain these events. The application of statistical models, either descriptive or inferential, helps on the process of fitting distributions to the failure data (Ebeling, 2010).

Problem Statement

For older fleets, ample data is available to study failures of parts and systems. Using many techniques available from reliability theory, this data can be used to calculate the probability of a failure of an item or system. Would it be possible to use the survival analysis to create a failure prediction model for the BAF T-27 Tucano fleet?

Methodology

Survival analysis is the study of the duration of life and has been broadly used in medical statistics to study the survivability of patients until the event of death (Cox & Oakes, 1984). The analysis informs how long would a patient survive or, in other words, what is the probability of death in an interval of time (Mills, 2011). Although people die only once in a life, recently some studies are using the recurrent events approach in case of survival analysis for patients with recurrent diseases. In the recurrent events approach, the time between events (or failures) becomes the focus of the survival analysis. In this study, the recurrent event approach is applied to recurrent failures. Non-parametric, semi-parametric, and parametric statistical models of the TBF such as the descriptive statistics, Kaplan-Meier estimators, Cox proportional hazards with or without frailty, and survival regression with or without frailty, are used. The data were collected from forty-five T-27 Tucano of the Brazilian Air Force (BAF). All the failures in a five-year interval were analyzed to compute the TBF.

Purpose Statement

This study attempts to identify which relationships are significant between system failures and the age of the of the BAF T-27 Tucano fleet by comparing various non-parametric, semi-parametric, and parametric statistical models to the TBF. In particular, the recurrent events approach is included in the comparisons.

Research Questions

The questions this study seeks to answer are: (a) How significant is the relationship between system failures and the age of the of the BAF T-27 Tucano fleet? (b) Is the use of the recurrent events approach going to change the significance of the relationship? (c) Is it possible to build a failure prediction model that can be applied to new airframes with similar configuration?

Assumptions/Limitations

In this study, the age of each aircraft is measured by the total flight hours since deployed. In addition, similar airframes are those with compatible mission, size, and design, for example, the BAF Tucano and the BAF Super-Tucano: both of them are small sized training aircraft equipped with a single engine. No other similar aircraft are considered in this study. It is assumed that all the forty-five aircraft picked for this research have the same configuration and are assigned to the same mission profile (training). Another assumption is that a type of failure can be identified by the workshop that fixes it, and each repair service means one aircraft failure. Lastly, it is also assumed that all the failures of all the aircraft are registered in the system and the information is correctly recorded.

Contributions

Very few studies tried to apply the recurrent event approach of survival analysis in to deal with machine failures. Hence, this research brought a novel application of the survival analysis as it was applied to build a model to predict aircraft failures.

The BAF T-27 Tucano

The design of the Tucano by Embraer started in 1977, with the first unit delivered in 1983. The Tucano (Figure 1) was originally designed for basic-training aircraft originally: a turbo-prop single engine and tandem ejection seats. The Tucano is stable in low speed but it is still acrobatic (Embraer, 2019).

Figure 1. BAF T-27 Tucano (Embraer, 2019)

Research Overview

This thesis is divided in five chapters: Introduction, Literature Review, Methodology, Analysis and Results, and the Conclusion and Recommendations. Chapter II contains a review of relevant studies on the survival analysis and the approaches adopted in this research. On Chapter III, the methodology, data collection, software, and survival analysis approaches used in this study are described. The analysis and results of the survival analysis are shown on Chapter IV segmented by Descriptive Summary, Kaplan-Meier, Cox PH, Survival Regression, and Frailty models. The research concludes in Chapter V with a discussion of the study, significance, and recommendations for future researches.

II. Literature Review

Chapter Overview

This chapter brings relevant studies on survival analysis, including non-parametric, semi-parametric, parametric, and frailty models. Most of the articles describe how the methodologies were applied to study the survival time of patients. Also, many articles showed how the frailty approach could be used to study recurrent diseases of patients. Thus, the review supports the statistical methodologies adopted in this research to develop different approaches of survival analysis applied to time between failures of aircraft.

Survival Analysis

Survival analysis examines the time until the occurrence of an event (Mills, 2011). Cox & Oakes (1984) define that survival analysis is a study of a group or groups of individuals to whom an event called failure may have happened. Similarly, Fox & Weisberg (2011) define survival analysis as the examination and modeling of the time until an event happens. Survival analysis is not a least-squared based regression model. Instead, it uses other likelihood estimators (Mills, 2011).

As this type of analysis is traditionally used in medical research, in which the called event is the death of the individual, the time until the occurrence of the event became the survival time, and that is the origin of the terminology (Fox & Weisberg, 2011). However, there are many other examples of events that can be studied such as machine part failures, employees strikes (Cox & Oakes, 1984), marriages, birth, and bank mergers (Mills, 2011). Ebeling (2010) gives another perspective when the survival function is compared to the reliability function, as both of them are the function of probabilities of a component (or an individual) that works during a certain period without a failure.

Hazard Rate Function

Also known as failure rate, the hazard rate function is often used in reliability studies. Survival models usually use the hazard function in order to account for the censored data as it adds information about timing (Fox & Weisberg, 2011; Mills, 2011). This function provides the rate of failure and the conditional probability of the failure in an interval of time ($t + \Delta t$) given that the individual has survived until time t without failure (Ebeling, 2010). Fox & Weisberg (2011) define the hazard function as the risk of failure at each instance. The hazard rate function is:

$$h(t) = \lim_{\Delta T \to 0} \frac{\Pr[(t \leq T < t + \Delta t) | T \geq t]}{\Delta t} = \frac{f(t)}{S(t)} \quad (1)$$

Where:

S(t) is the survival function

T is the random variable of survival time

f(t) is the density function

Making assumptions about the shape of the hazard rate function or about how the covariates modify that shape is what define if the model is non-parametric, semi-parametric or parametric (Mills, 2011). Another approach that may affect the survival analysis is taking in account the recurrence of events for each individual, which is called a frailty model (Hougaard, 1995).

Non-Parametric Models

The non-parametric survival models do not make any assumptions about the shape of the hazard rate function (Mills, 2011). Also known as distribution-free methods, these empirical methods produce the failure distribution and hazard rate function directly from the times to failure (Ebeling, 2010). This is the preferred method when the data do not fit any of the most known distributions.

The most basic way to understand the data is computing descriptive statistics summary. However, the measures of central tendency (such as the mean) alone are not sufficient to describe data or probability distributions. It is necessary to calculate the variance of data for estimating the likelihood within a certain confidence interval of time to failure (McClave et al., 2014).

The Kaplan-Meier (KM) estimate of survival is another non-parametric model in which the product-limit estimator is calculated from the maximum likelihood arguments (Cox & Oakes,1984). It is a widely used methodology to calculate the empirical reliability function (Ebeling, 2010). Even though it is possible to stratify data with the KM method, it does not allow the inclusion of covariates in the model (Mills, 2011).

Semi-Parametric Model

In this study, the semi-parametric approach adopted is the Cox proportional-hazard (PH) model. While still not making any assumptions about the shape of the hazard rate function, the Cox PH model allows covariates and makes strong assumptions on how the covariates may affect the shape of the hazard function (Mills, 2011). The meaning of proportional hazards here regards to how the covariates changes the failure rate as it can be a multiplicative relationship (Ebeling, 2010). Mills (2011) also explains that the Proportional Hazard means that each individual will have its hazard fixed as a proportion of the hazard of the other individuals.

Another distinction of the Cox PH model is the use of the partial likelihood method. While the KM model uses the maximum likelihood estimation method, the Cox PH model adopts "partial likelihood", in which the likelihood is calculated considering only the individuals that had at least one failure (Fox & Weisberg, 2011).

Although it is not a precise approach like the parametric method, the Cox PH model generally fits well to data without specifying an underlying-probability distribution. Nonetheless, it is still possible to calculate parameter estimates that can be used to asses how the covariates affect the hazard model (Cox & Oakes, 1984).

Parametric Models

The parametric models assume what should be the hazard function distribution in advance, which allows more precise parameter estimates and predictive modeling. It means that the model assumes how the covariates affect the shape of the hazard function (Mills, 2011). Gutierrez (2002) explains that the "parametric survival models are regression models in which the distribution of the response is chosen to be consistent with what one would see if the response is time-to-failure." The parametric models in this study is the survival regression with the Weibull distribution fit.

Frailty Model

A frailty model is applied to survival analysis in order to account for the repeated failures (events) that have occurred to the same individual. As known as “a random effect approach”, the frailty model does not ignore the correlation between the recurrent events for each subject. Instead, it adds a covariate to the model in order to create some dependence between those events (Amorim, 2014). Munda et al. (2012) explains that the frailty model accounts for the different risk levels that may affect the individuals, so it is nothing more than an “extension of the proportional hazards model in which the hazard function depends upon an observable random quantity.” Hougaard (1995) says that, in the frailty model, both the hazard function and the frailty (called the random effect) are the causes of the variability of the time to failure.

The frailty approach is not exclusively applied to parametric models. It can be applied to semi-parametric models too (Munda et al., 2012). In the parametric model, the failure times have a parametric density that results in a defined baseline when the frailty approach is applied while the baseline stays unknowns in the Cox PH model (Munda et al., 2012).

Summary

The literature shows how the survival analysis can be used to study the time until an event happens, and the time between events (in case of recurrent events). There are not many studies applying the frailty model to aircraft failures. This research seeks to fill this gap and apply the survival analysis to the time between failures of the BAF T-27 Tucano fleet.

III. Methodology

Chapter Overview

This study attempts to identify how significant is the relationship between system recurrent failures and the variables using survival analysis through various statistical approaches. Among them, the frailty approach applied to the repeated failures of each aircraft for assessing the significance of the covariates such as the TBF and the time since new (TSN) of the BAF T-27 fleet.

This chapter describes the research methodology for analyzing the numerical data and building statistical analysis. After that, there is an outline of the data and variables, explaining the data collection, variables, and a brief statistical summary of the TBF entries in this study. Chapter III concludes with a discussion of each one of the Survival Analysis approached used in this study.

Research Methodology

The main subject of this study is the times between aircraft failures. This study uses survival analysis including non-parametric, semi-parametric, and parametric (Survival Regression, Frailty) models that explain the survivability of the BAF Tucano fleet. It is possible to (a) examine trends and differences between the chosen variables using the non-parametric models, (b) identify significant factors that affect the TBF with semi-parametric survival analysis, and (c) predict failures using the parametric approach, followed by the comparison of the semi-parametric and the parametric results. The goodness of fit analysis compared the models' fit and is used for model selection.

Data and Variables

The BAF uses the Logistics & Maintenance Integrated System (SILOMS) is the database that aggregates almost all information related to maintenance and logistics including the log of all the services done on each equipment. The primary data of this study are all repair entries of each aircraft, all retrieved from SILOMS. Each entry includes the tail number, the workshop, the calendar date of the failure, and the time since new (TSN) in flight hours at that time, among others. In addition, each repair done on the aircraft is counted as one aircraft failure.

The first criterion to choose the T-27 was the fact that there is plenty of data of this fleet in the system. The next criterion is the tail numbers that has the same mission profile during the five years from January 2013 to December 2017. As a result, the final data set includes 1,119 entries for the failures of forty-five aircraft from the BAF Tucano fleet. It is important to clarify that an individual aircraft may have entered the group after 2013 or may have left the group before 2017.

From the raw data, this study focuses on five variables of interest: identification (ID), system, time since new (TSN), time between failures (TBF), and status (failure =1, non-failure = 0). The variable system is categorical and includes three treatments (or factors) such as AVIONICS, ELECTRIC, and ENGINE, which are three systems of the aircraft. The variable ID is equivalent to the tail numbers that is classified information and was removed from the data set. Descriptive statistics on time between failure (TBF) are presented in Table 1.

Table 1. Descriptive Statistics Time Between Failure entries

	TIME BETWEEN FAILURES (TBF)			
	AVIONICS	ELECTRIC	ENGINE	ALL
Range	415.500	456.420	482.750	482.750
Minimum	2.920	0.160	0.080	0.080
Maximum	418.420	456.580	482.830	482.830
Sum	7021.800	34415.250	22432.060	63869.110
Count (# of failures)	130	610	379	1119

Survival Analysis

Four different approaches of the survival analysis are used in this study: non-parametric, semi-parametric, parametric, and frailty models. The descriptive statistics summary and the Kaplan-Meier estimates, including the stratification by systems, are the non-parametric models, while the Cox Proportional-Hazards (PH) is the semi-parametric model, the survival regression is the parametric model, and the frailty approach was added to both Cox PH and survival regression to study recurrent events.

Non-Parametric Models

The descriptive statistics are presented first. The non-parametric method used in this research is the Kaplan-Meier (KM) estimate of survival. Using all TBF entries with or without factors (systems), survivor curves, life tables, and KM estimates are computed. The KM estimates are the surviving probabilities of an individual for a particular time while the KM survivor curve shows the survival probability *versus* the TBF. All results are obtained using the R statistical packages (R, 2019). The package “Survival” mainly deals with survival analysis (Mills, 2011). The Kaplan-Meier estimator model is defined by:

$$\hat{S}(t_j) = \hat{S}(t_{j-1}) \times \Pr(T > t_j | T \geq t_j)$$

Where:

$S(t_j)$ is the survival function at failure time t_j

T is the random variable of survival time (T ≥ 0)

Semi-Parametric Model

A Cox proportional hazard method, which is a semi-parametric model that does not assume an underlying-probability distribution, is used in this study (Mills, 2011). In this method, the failure of an aircraft (STATUS) was the dependent variable. TBF, AVIONICS, and ELECTRIC were the independent variables. AVIONICS and ELECTRIC were dummy variables indicating workshops (or systems). Accordingly, when AVIONICS and ELETRIC took zeros, the model became the baseline model for ENGINE. TSN was used for indicating time in the model. The Cox PH model is defined by:

$$\frac{h_i(t)}{h_j(t)} = \exp\{\beta_1(x_{i1} - x_{j1}) + \cdots + \beta_k(x_{i1} - x_{j1})\}$$

Where:

$h_i(t)$ is the hazard for individual *i* at time *t*

β_k is the coefficient of the *k-th* covariate

Parametric Model

Survival regression is used in this research as a parametric approach to the data. Parametric models assume a specific function in addition to how the variables affect the hazard function (Mills, 2011). This study assumes that the hazard function has the Weibull distribution. The variables were treated in the same way as in the Cox-PH model. STATUS was the dependent variable, and TBF and two dummy variables were the independent variables. TSN was a time indicator. The survival regression model with the Weibull distribution fit is defined by:

$$\hat{S}(t) = \exp(-\lambda_j t_j^p)$$

Where:

$\hat{S}(t)$ is the survival function with the Weibull distribution fitting

λ_j is the Weibull distribution scale parameter

p is the Weibull distribution shape parameter

Frailty Model

A frailty or recurrent event model explicitly considers repeated failures (events) that occurs in each tail number (ID). Hence, for each ID, the number of events was taken into account in addition to how the variables change between the events (Mills, 2011). Regarding the variables, frailty treatment required including the variable ID in the Cox-PH and Survival Regression models. The purpose of this procedure was to investigate the assumption that the frailty of recurrent events would change the results of the survival analysis.

If there are j subjects in i subgroups, then, with the frailty approach, the hazard function will be:

$$h(t_{ij}) = h_0(t)\exp(\beta' x_{ij} + \psi' \omega_j)$$

Where:

h_0 is the baseline hazard function

x_{ij} is the covariate vector

β is the regression parameters vector

ψ is the group-level heterogeneity

ω_j is the subgroup of frailties

The R language and environment

R is a software that has packages and functions designed to analyze data in many different ways (R, 2019). In this research, the survival packages were used for obtaining the results of the 19 survival models.

The *survfit* function was used to obtain the Kaplan-Meier estimates with and without the stratification by systems or workshops such as ENGINE, AVIONICS, and ELECTRIC. The inputs in this case were the TBFs and the STATUS, which is 1 for all the entries as all the events in this research are failures. For the Cox PH survival analysis, the function *coxph* was used. The inputs were the TSN and STATUS with the covariates such as TBF, AVIONICS, and ELECTRIC. The dummy variables AVIONICS and ELECTRIC took zeros to have the baseline model for ENGINE. For the survival regression with the Weibull distribution, the function *survreg* was used with the same covariates in the Cox

PH. To add frailty in the model, the covariate ID was included in both Cox PH and Survival Regression models.

Summary

Although there are many medical studies that apply the survival analysis to the survival of patients, there is almost no survival study available for aircraft. This research brings a different utilization of the theory as the study applies it to study failures of the BAF Tucano aircraft. Also, when applying the frailty approach, this research brings a novel utilization of the survival analysis for recurrent events.

IV. Analysis and Results

Chapter Overview

In this chapter the results for each of the survival models used in the study are shown. By utilizing non-parametric models, semi-parametric, and parametric models, this study analyzes failures of the BAF T-27 Tucano aircraft and provides the results to answer the research questions.

The findings are relevant as the Frailty approach shows to be adequate and changes the statistical significance of the variables in comparison to the other models that do not consider the failures as recurrent events.

Survival Analysis

Descriptive Statistics

Table 2 shows descriptive statistics for the variable. From the analysis of the data for each one of the systems, and the whole TBF entries in the study, it is possible to observe that the AVIONICS and ELECTRIC systems show results quite similar to those for the whole TBF data, while the ENGINE system shows results more distant from the whole TBF data. The mean TBF differ from the median by approximately 20 hours explained by the high Skewness of the data.

In addition, the histogram in Figure 2 displays an actual visualization of the data in the study. Figure 2 also shows the highest frequency of failures occurred in up to 20 flight hours with 381 events followed by 238 failures between 20 and 40 flight hours. These numbers are consistent with the values of the median and mean presented in Table 2.

Table 2. Descriptive Statistics for the Time Between Failure

	TIME BETWEEN FAILURES (TBF)			
	AVIONICS	ELECTRIC	ENGINE	ALL
Mean	54.014	56.418	59.187	57.077
Standard Error	5.255	2.460	4.050	2.012
Median	36.875	35.415	29.500	34.000
Mode	14.840	54.330	0.500	6.750
Standard Deviation	59.911	60.758	78.854	67.307
Sample Variance	3589.336	3691.570	6217.904	4530.171
Kurtosis	12.476	7.985	8.066	9.129
Skewness	2.944	2.251	2.641	2.586
Range	415.500	456.420	482.750	482.750
Minimum	2.920	0.160	0.080	0.080
Maximum	418.420	456.580	482.830	482.830
Sum	7,021.800	34,415.250	22,432.060	63,869.110
Count	130	610	379	1119

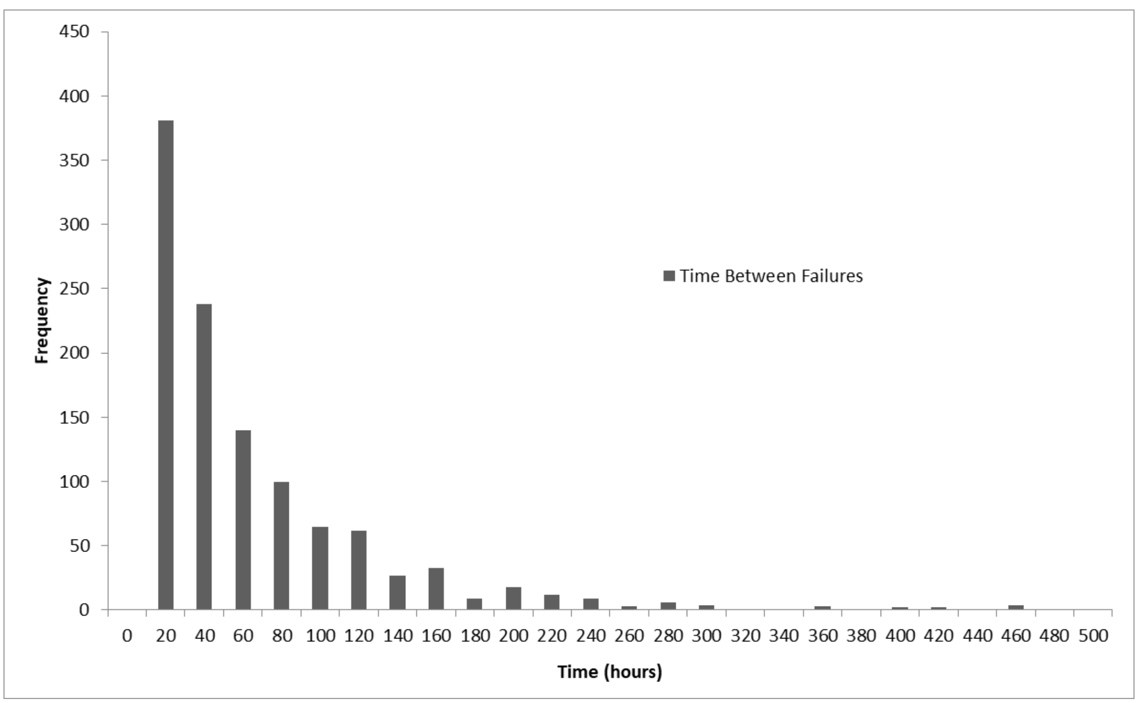

Figure 2. Histogram of the Time Between Failures

Kaplan-Meier Estimator

Table 3 shows Kaplan-Meier estimators computed using the survival function in R, with the default type of censoring, TBF for the time variable, the event indicator (STATUS), log confidence intervals, and Greenwood variance method. The survival probabilities are consistent with the results obtained in the descriptive statistics as the medians (TBF = 34.00 hours) are the same in both methods.

Table 3. Kaplan-Meier Estimates for Time Between Failures

	Survival Probability		
	25%	50%	75%
Lower 0.95 CL	71.08	30.91	11.92
Quantile	76.42	34.00	13.50
Upper 0.95 CL	83.75	37.34	15.00

According to the model, it is possible to verify that the probability of having TBF between 71.08 and 83.75 hours is 25 percent, while the probability of having TBF between 11.92 and 15.00 hours is 75 percent. Figure 3 and Figure 4 shows the plot of survival curves for all the calculated Kaplan-Meier estimates in detail.

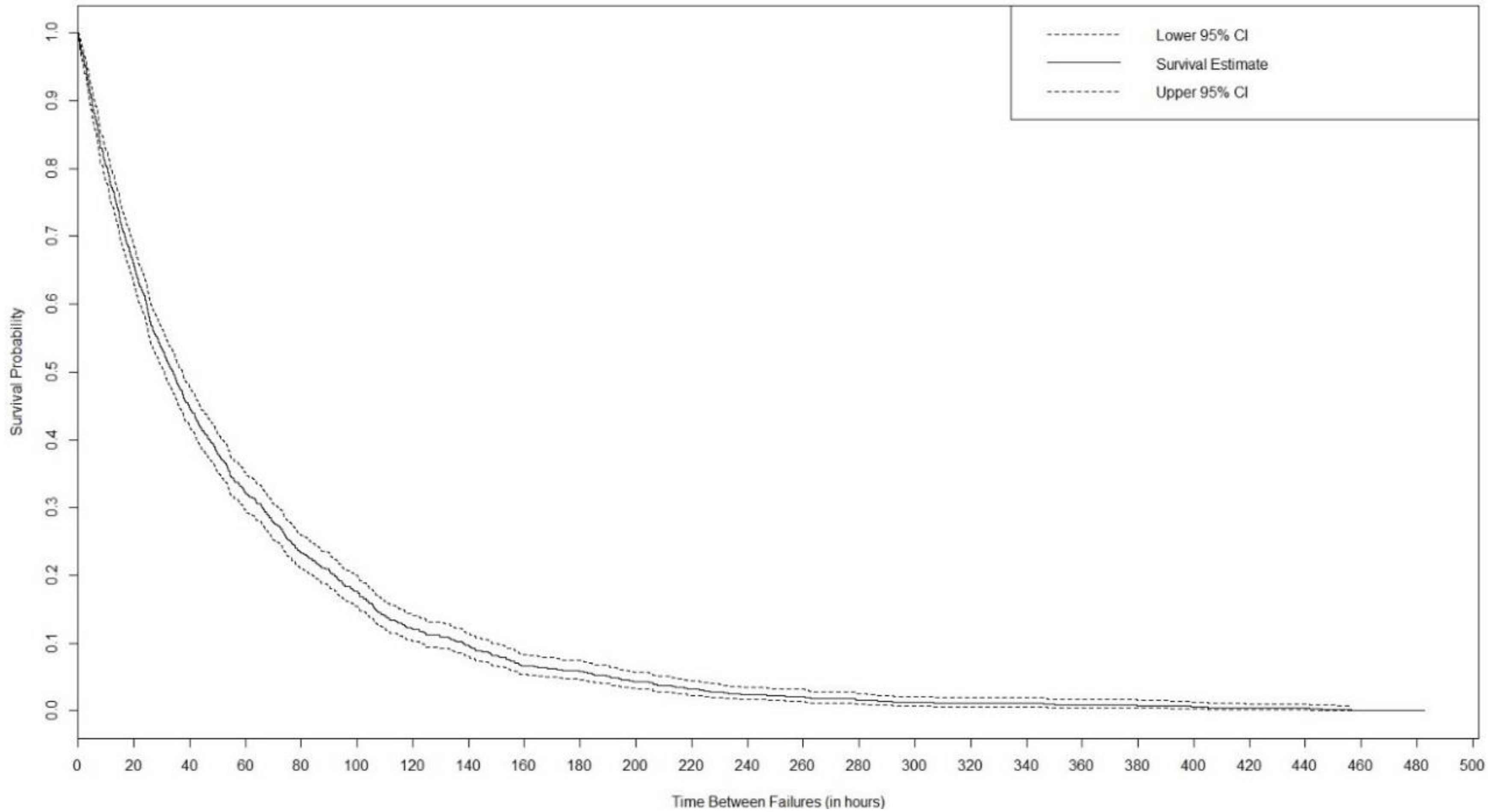

Figure 3. Kaplan-Meier Survival Curve for Time Between Failures

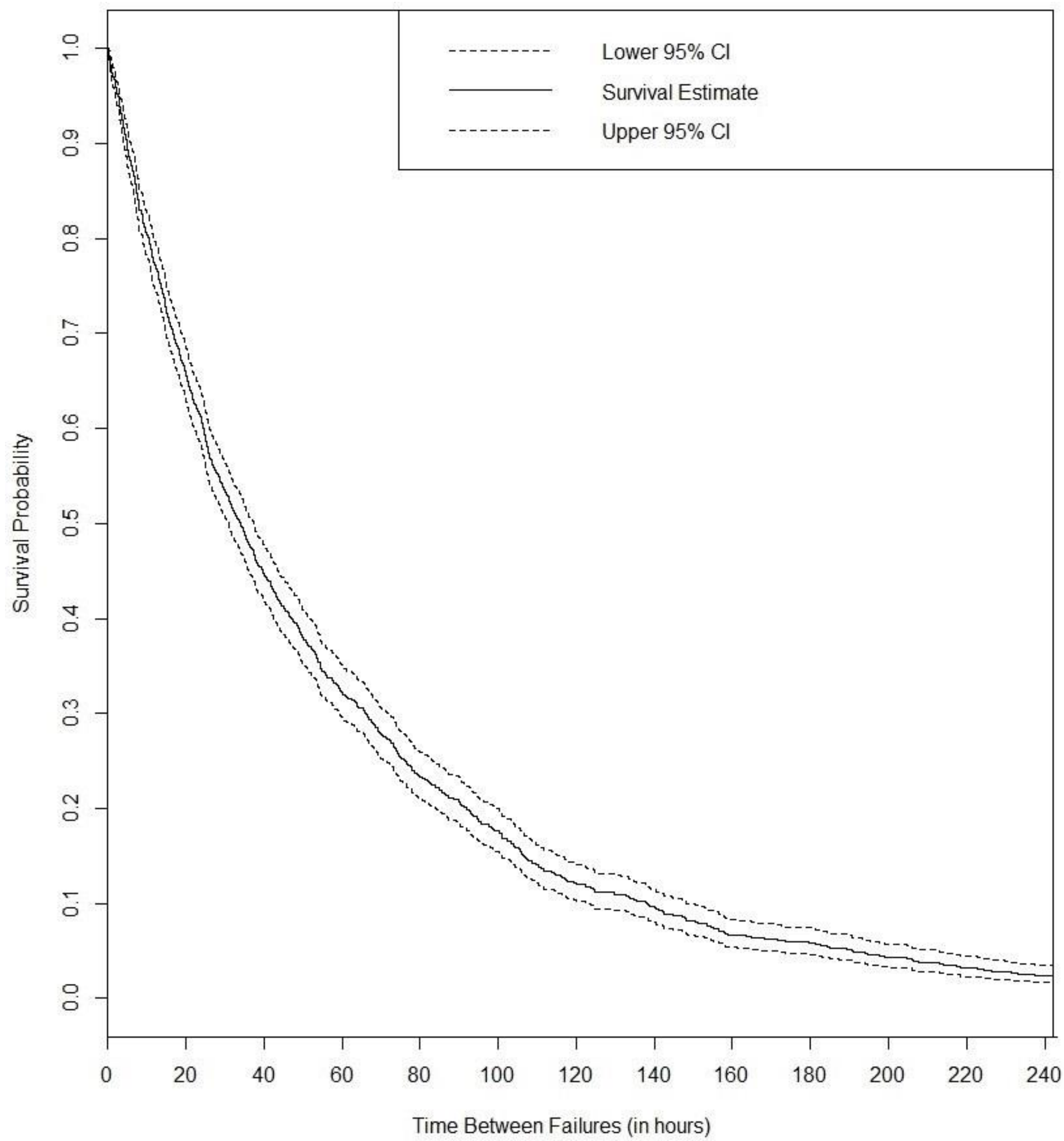

Figure 4. Kaplan-Meier Survival Curve in detail

Kaplan-Meier Estimator (per system)

Table 4 shows results of Kaplan-Meier estimators computed using the survival function in R as well, same configuration used before, but stratified by systems (stayed the same: the default type of censoring, TBF as the time variable, and the event indicator STATUS = 1 for all the entries as all the entries are failures, log confidence intervals, and greenwood variance method). The survival probabilities are consistent with the results obtained in the descriptive statistics as the medians for all systems are the same in both methods.

Table 4. Kaplan-Meier Estimates for Time Between Failures Stratified by Systems

	Survival Probability (per system)								
	AVIONICS			ELECTRIC			ENGINE		
	25%	50%	75%	25%	50%	75%	25%	50%	75%
Lower 0.95 CL	56.25	28.42	11.33	73.08	31.50	11.58	63.92	25.58	9.66
Quantile	69.08	36.88	14.84	77.83	35.42	13.59	73.25	29.5	12.67
Upper 0.95 CL	87.25	49.25	23.33	87.25	41.41	15.67	92.84	35.91	16.83

Additionally, according to the model, it is possible to verify that the probability of the AVIONICS variable to have TBF between 56.25 and 87.25 hours is 25 percent while the probability of having TBF between 11.33 and 23.33 hours is 75 percent. The plot of all the calculated Kaplan-Meier estimates shows the survival curve of each system. In this case, the confidence intervals were not plotted to preserve the visibility of results. Figure 5 and Figure 6 present the survival curves in detail.

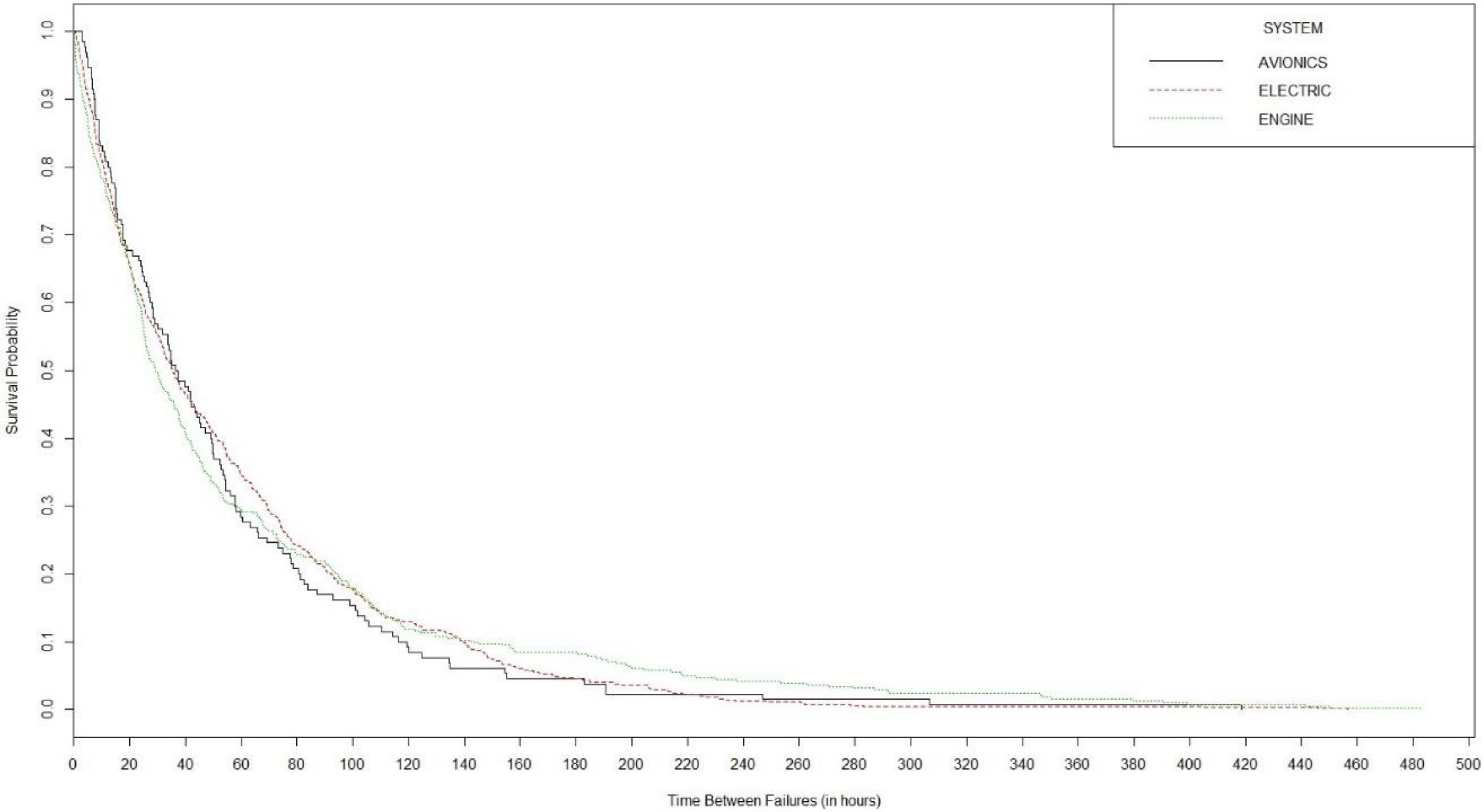

Figure 5. Kaplan-Meier Survival Curve for TBF stratified per system

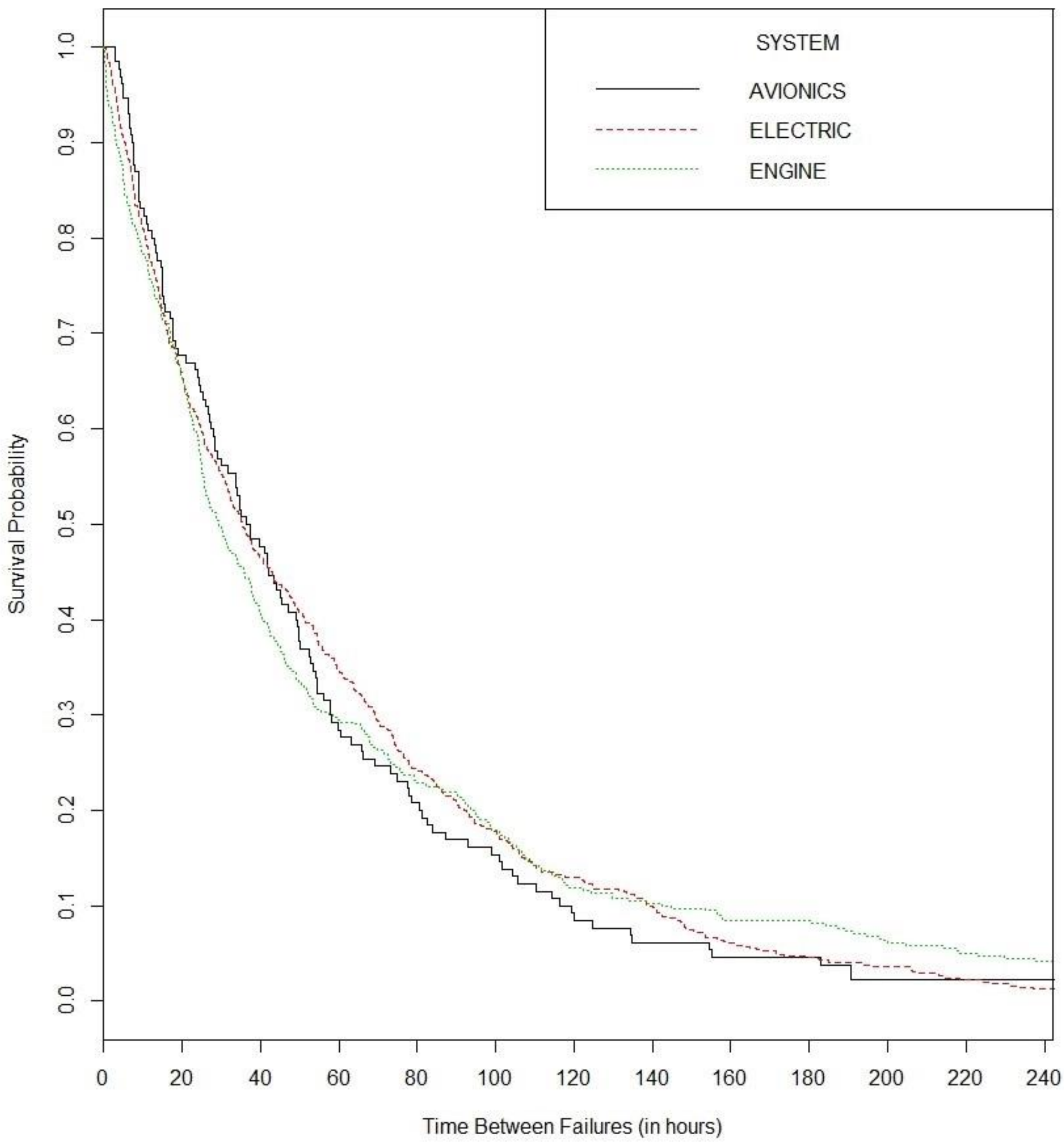

Figure 6. Kaplan-Meier Survival Curve stratified per system in detail

Cox Proportional-Hazards

The Cox PH model on Table 5 resulted from the Cox regression fit function in R, with the default type of censoring, TSN as the time variable, the event indicator STATUS = 1 for all the entries as all the entries are failures, Efron method for ties, and the default robust standard errors.

Each of the four models brings variations on the interaction between the variables TBF, AVIONICS, and ELECTRIC:

- Model 1: Surv(TSN, STATUS) ~ TBF + AVIONICS + ELECTRIC;
- Model 2: Surv(TSN, STATUS) ~ TBF * AVIONICS + ELECTRIC;
- Model 3: Surv(TSN, STATUS) ~ TBF * AVIONICS + TBF * ELECTRIC;
- Model 4: Surv(TSN, STATUS) ~ AVIONICS + TBF * ELECTRIC.

None of the variables are significant on the four models for $p \leq 0.05$ (95 percent confidence). The Cox PH regression does not seem to be suitable to explain the TBF and TSN. Still, the AIC test showed that Model 1 is better than the three other models.

Table 5. Cox Proportional-Hazards Regression results

	COX PROPORTIONAL-HAZARDS							
	MODEL 1 Coefficients	*p*	MODEL 2 Coefficients	*p*	MODEL 3 Coefficients	*p*	MODEL 4 Coefficients	*p*
TBF	-0.00024	0.60290	-0.00037	0.44000	-0.00045	0.50300	-0.00020	0.74340
AVIONICS	0.19378	0.05850	0.10365	0.44500	0.09877	0.47500	0.19421	0.05820
ELECTRIC	0.05293	0.42030	0.05252	0.42400	0.04288	0.61700	0.05767	0.49520
TIME * AVIONICS	-	-	0.00173	0.29100	0.00181	0.28800	-	-
TIME * ELETRIC	-	-	-	-	0.00017	0.86100	-0.00008	0.92900
AIC	13484.19		13485.14	-	13487.11	-	13486.18	-

Survival Regression

The Survival Regression model on Table 6 resulted from the parametric survival fit function in R, with the default type of censoring, TSN as the time variable, and the event indicator STATUS = 1 for all the entries as all the entries are failures, Weibull distribution fit, and default robust standard errors.

Each of the four models brings variations on the interaction between the variables TBF, AVIONICS, and ELECTRIC:

- Model 5: Surv(TSN, STATUS) ~ TBF + AVIONICS + ELECTRIC;
- Model 6: Surv(TSN, STATUS) ~ TBF * AVIONICS + ELECTRIC;
- Model 7: Surv(TSN, STATUS) ~ TBF * AVIONICS + TBF * ELECTRIC;
- Model 8: Surv(TSN, STATUS) ~ AVIONICS + TBF * ELECTRIC.

None of the variables are significant on the four models for $p \leq 0.05$ (95 percent confidence). The survival regression itself does not seem to be suitable to explain the TBF and TSN, but the AIC test showed that Model 5 is better than the three other models.

Table 6. Survival Regression - Weibull Fit results

	SURVIVAL REGRESSION - Weibull Fit							
	MODEL 5 Coefficients	*P*	MODEL 6 Coefficients	*p*	MODEL 7 Coefficients	*p*	MODEL 8 Coefficients	*P*
Intercept	9.17887	<2e-16	9.17683	<2e-16	9.17482	<2e-16	9.17883	<2e-16
TBF	0.00008	0.50000	0.00012	0.35000	0.00015	0.39000	0.00008	0.61000
AVIONICS	-0.04284	0.11000	-0.01719	0.64000	-0.01518	0.68000	-0.04283	0.12000
ELECTRIC	-0.00983	0.57000	-0.00968	0.58000	-0.00565	0.80000	-0.00973	0.66000
TIME * AVIONICS	-	-	-0.00049	0.27000	-0.00053	0.25000	-	-
TIME * ELECTRIC	-	-	-	-	-0.00007	0.78000	0.00000	0.99000
Log(scale)	-1.32120	<2e-16	-1.32197	<2e-16	-1.32194	<2e-16	-1.32120	<2e-16
Loglik	-10377.10	-	-10376.50	-	-10376.50	-	-10377.10	-
Loglik (Intercept)	-10378.60	-	-10378.60	-	-10378.60	-	-10378.60	-
Chi sq	3.00	-	4.15	-	4.22	-	3.00	-
AIC	20764.14	-	20765.00	-	20766.92	-	20766.14	-

Frailty Models

The results of the Cox PH model with the frailty approach are in Table 7, while the results of the survival regression with frailty are in Table 8. To apply the frailty approach, the factor "frailty(ID)" must be added to the formula in R so that it will account for the recurrence of the events for each aircraft (ID).

The description of the eight Frailty models are:

- Models 9 and 13: TSN ~ TBF + AVIONICS + ELECTRIC + frailty(ID);
- Models 10 and 14: TSN ~ TBF * AVIONICS + ELECTRIC + frailty(ID);
- Models 11 and 15: TBF * AVIONICS + TBF * ELECTRIC + frailty(ID);
- Models 12 and 16: AVIONICS + TBF * ELECTRIC + frailty(ID).

Table 7. Cox Proportional-Hazards Regression (with Frailty) results

	COX PROPORTIONAL-HAZARDS WITH FRAILTY							
	MODEL 9 Coefficients	*p*	MODEL 10 Coefficients	*p*	MODEL 11 Coefficients	*p*	MODEL 12 Coefficients	*P*
TBF	0.00003	0.95000	0.00030	0.55000	-0.00041	0.54000	-0.00073	0.24000
AVIONICS	0.37329	0.00058	0.51302	0.00023	0.46859	0.00096	0.37030	0.00064
ELECTRIC	0.04565	0.51000	0.04449	0.53000	-0.04900	0.59000	-0.06427	0.47000
TIME * AVIONICS	-	-	-0.00247	0.13000	-0.00177	0.30000	-	-
TIME * ELETRIC	-	-	-	-	0.00163	0.09700	0.00193	0.04200
AIC	9864.11		9863.48	-	9862.61	-	9861.81	-

Table 8. Survival Regression – Weibull fit (with Frailty) results

	SURVIVAL REGRESSION WITH FRAILTY- Weibull Fit							
	MODEL 13 Coefficients	*p*	MODEL 14 Coefficients	*p*	MODEL 15 Coefficients	*p*	MODEL 16 Coefficients	*P*
Intercept	9.06479	<2e-16	9.06537	<2e-16	9.06291	<2e-16	9.06236	<2e-16
TBF	0.00000	0.83450	-0.00002	0.53300	0.00003	0.44870	0.00004	0.24900
AVIONICS	-0.01729	0.00140	-0.02283	0.00100	-0.02024	0.00420	-0.01702	0.00160
ELECTRIC	-0.00392	0.26220	-0.00388	0.26700	0.00149	0.73930	0.00200	0.65130
TIME * AVIONICS	-	-	0.00010	0.22500	0.00006	0.48920	-	-
TIME * ELECTRIC	-	-	-	-	-0.00009	0.05680	-0.00010	0.02900
Log(scale)	-2.98918	<2e-16	-2.98923	<2e-16	-2.99068	<2e-16	-2.99077	<2e-16
Loglik	-8537.30	-	-8536.50	-	-8534.70	-	-8534.90	-
Loglik (Intercept)	-10378.60	-	-10378.60	-	-10378.60	-	-10378.60	-
Chi sq	3682.56	-	3684.17	-	3687.81	-	3687.31	-

The results now show that some variables and interaction between variables are significant on the models for $p \leq 0.05$ (95 percent confidence). Considering the Cox PH models with frailty, by comparison of the AIC, Model 12 should be the best (it has the lowest AIC). On the other hand, regarding the survival regression models with frailty, by comparison of the Chi-Squared, Model 13 should be the best (it has the lowest Chi Sq). However, yet sticking with the 95 percent confidence interval, Model 16 shows one more significant variable, the interaction between TIME and ELECTRIC. Since it is not possible to calculate the AIC for the survival regression model with frailty, other methodology should be necessary to choose the best model between the Cox PH with frailty or the survival regression with frailty.

Summary

Based on the results presented in Table 2 to Table 8, it was possible to verify that the variables could be strongly significant depending on the survival model. The major finding in this research is the fact that the frailty approach changed how the variables and their interaction are significant. This study proved that as the recurrent events become part of the analysis, the variables became significant to the models both Cox PH and survival regression models.

In this study, the survival regression with Weibull fit and frailty seems to be the best model as it has more significant variables considering the 95 percent confidence level. As it is a parametric model, the coefficients of the model are also the coefficients of the failure prediction function. More research should be done to find how good are the predictions when applied to new airframes that are similar to the BAF T-27 Tucano.

V. Conclusions and Recommendations

Conclusions

It was possible to verify that the variables can be very significant depending on the survival model. The major finding in this study was the fact that the frailty approach changed how significant were the variables and their interaction. This study proved that as the recurrent events became part of the analysis, the variables became significant to both Cox PH and survival regression models.

In this study, the survival regression with Weibull fit and frailty seems to be the best model as it has more significant variables considering the 95 percent confidence level. As it is a parametric model, the coefficients of the model are also the coefficients of the failure prediction function. More studies should be done to find how good are the predictions when applied to new airframes that are similar to the BAF T-27 Tucano.

Significance of Research

This study attempted to apply survival analysis using different approaches to examining the time between failures (TBF) of the BAF T-27 Tucano fleet. While these techniques have been widely used in the medical field, this paper shows that the TBF and failures events of aircraft can be used in the same way as the survival time and recurrent diseases for patients. The research also tried to confirm statistically significant variables in the survival models.

Recommendations for Future Research

The parametric models explored in this research are the keys to building failure prediction models. Future research should examine how good are these predictions, in particular, when applied to the new airframes. Adaptive predictions are also an acceptable approach for new airframes as new data are collected, more data can be added to the prediction models, and they can be adapted to the new scenario. Another topic that is worthy to be explored is the relationship between TBF and the number of sorties during the interval of time.

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14. ABSTRACT

During the life of an aircraft, several failures may occur causing unplanned maintenance and costs of parts, labor, transportation, lost opportunities, and operations, among others. The prediction of these events becomes especially difficult for new airframes, since they do not have many flight hours or enough data to observe failures. This study analyzes and model the time between failures (TBF) of the Brazilian Air Force T-27 Tucano fleet by applying various non-parametric, semi-parametric, and parametric statistical models, to the TBF, such as the descriptive statistics, Kaplan-Meier estimators, Cox proportional hazards models, with or without frailty, and survival regression models, with or without frailty. The study concludes by proposing a failure model that can be applied to the new similar airframes.

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U	U	U	UU	45	(937) 255-3636, ext 4702 daniel.steeneck@afit.edu

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